Pedestrian Tracking using a Generalized Potential Field Approach

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Abstract: Mobile robots and autonomous driving cars operate in a shared environment with pedestrians. In order to avoid accidents, it is important to track and predict human trajectories in an optimal way. In this paper, a generalized potential field approach for characterizing pedestrian movements is proposed which goes beyond the well-known social force model. Its goal is to give a generalized architecture for improving the tracking accuracy of pedestrians in surveillance situations. In comparison to other fusion approaches, the number of proposed parameters is reduced and the parameters can be intuitively understood. For a simple scenario, in a forum the trajectories of pedestrians are predicted for a configured parameter set. For this purpose, the proposed model is used. The predicted trajectories are compared to the real trajectories of the pedestrians. First results regarding the accuracy of the approach are presented.

1 INTRODUCTION

In the field of robotics and autonomous driving cars vehicles or robots often have to interact with pedestrians. To assure that the risk for pedestrian is minimal, it is very important to track pedestrians in a precise way. Camera based sensors are mostly used in closed rooms, especially in surveillance areas. Tracking of dynamic objects by cameras is a recent research topic (Ibisch et al., 2015).

To improve tracking accuracy, many different models for pedestrians have been proposed over the last decades. Fluid-dynamic models were used to describe the macroscopic behavior of pedestrians. In (Helbing, 1998) a Boltzmann-like gas-kinetic model was introduced, which was motivated by good results in traffic flow simulation (Alberti and Belli, 1978; Prigogine, 1900), but the model neglects the individual behavior of pedestrians. In the microscopic field, Markovian models were developed to differentiate between different pedestrians states like standing, walking and running (Wakim et al., 2004). For computational issues, grid cell based approaches were introduced (Dijkstra et al., 2001), which are based on the class of cell automata models. A specialization of this class is the floor field approach (Ali and Shah, 2008), which combines the interaction of pedestrians in crowded scenes with the environment. For the floor field approach, frameworks of pedestrian crowd simulation were developed (Kretz and Schreckenberg, 2006). Another microscopic and physical approach is the social force model (Dirk Helbing and Peter Molnar, 1995), which describes every human interacting in a field of social forces. These social forces are defined by other pedestrians and the environment. The social force model proposes every pedestrian aims to have an individual velocity in a certain direction.

Beside the proposed models, an extensive research in using the different information sources for predicting trajectories or improving the tracking of pedestrians is performed. Recent research often focuses on intention prediction (Bandyopadhyay et al., 2013b; Bandyopadhyay et al., 2013a) for optimal motion planning or the decision process of crossing the street (Keller and Gavrila, 2014). Other research is based on dynamic object interactions and planning (Heinemann et al., 2006). But often only one or two information sources (e.g. intention or environment) are considered and the approaches can not easily be generalized.

Frameworks, which give a generalized architecture for the fusion of many information sources typically consist of settings with many parameters. These parameters often can not be intuitively understood and have to be trained by machine learning algorithms. Typical examples of approaches with at least ten parameters are (Heinemann et al., 2006; Robin et al., 2009; Yi et al., 2015). In this paper, a phys-

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ical model based on the social force model is motivated, which tries to minimize the number of parameters. Furthermore, the value of the parameters doesn't have to be learned by trajectories of real scenarios, but can be intuitively understood and configured.

This paper is organized as follows. In section 2 the model is proposed, in section 3 a pedestrian prediction model is derived, which includes the proposed dynamical model. With this pedestrian prediction model trajectories are generated, which are compared with real observed trajectories. The evaluation is discussed in section 4, in section 5 further steps of future research are presented.

2 PROPOSED MODEL

The model is driven by the idea to improve classic tracking algorithms like Kalman Filter or Monte Carlo Methods through the fusion of available information sources. These information sources could be the environment, dynamic object interactions, intention, that are the goals of the pedestrians (Tamura et al., 2012) or crowd effects (Yi et al., 2015). The model is based on the assumption that pedestrians act like test particles in a potential field. The goal of the model is the calculation of the person's acceleration resulting from the corresponding potential field.

2.1 Calculation of Potential Field

As mentioned before, every pedestrian acts like a test particle in each potential field. Each potential field ϕ^k represents an information source (e.g. enviroment is represented as a map) and is the combination of n^k potential sources ϕ_i^k (e.g. wall in the map). The potential at the position of the pedestrian is calculated by the weighted sum of ϕ_i^k potentials, which can be interpreted as contour lines, at the position $P^k(x_i, y_i)$ in the distance d_{iN}^k between the pedestrian and the potential source ϕ_i^k. The potential ϕ_N^k at the position of the pedestrian $P_N(x_N, y_N)$ with the weight p^k can be interpolated according to (Niemeier, 2008, S. 411). The weight p^k is assumed to be dependent on the distance to the pedestrian d_{iN}^k, but independent of time.

$$\phi_N^k = \sum_{i=1}^{n^k} p^k(d_{iN}^k)\phi_i^k \tag{1}$$

The distance d_{iN}^k to the pedestrian in two dimensional space is calculated by the euclidean distance:

$$d_{iN}^k = \sqrt{(x_i^k - x_N^k)^2 + (y_i^k - y_N^k)^2} \tag{2}$$

2.2 Derivation of Acceleration Vector

The acceleration vector of a particle in the potential field ϕ^k, produced by the information source k, is derived from the gradient of the potential field. The gravitation field is used as starting point for derivation.

For a mass m_P in a gravitation field the following applies (Lüders, 2008, S. 209), (Sigloch, 2009, S. 41)

$$\vec{F}_G(\vec{r}) = -m_P\vec{\nabla}\phi(\vec{r}) = m_P\vec{a}(\vec{r}) \tag{3}$$

$$\vec{\nabla}\phi(\vec{r}) = -\vec{a}(\vec{r}) \tag{4}$$

$\vec{F}_G(\vec{r})$ denotes the gravity force in dependence of distance $\vec{r}$ and $\vec{a}(\vec{r})$ denotes the acceleration in distance $\vec{r}$. As the proposed potential field is only a *pseudo* potential field, a normalization constant has to be introduced. In the following, it is denoted as **pseudo mass** m_p, which is a pedestrian dependent constant. Hence, (4) can be rewritten with the introduced nomenclature of section 2.1 as

$$\vec{\nabla}\phi_N^k = -m_p\vec{a}_N^k \tag{5}$$

$\vec{a}_N^k$ denotes the acceleration vector of source k at position P_N. As a consequence of (5) a pedestrian would increase to infinite speed for a constant decreasing potential. But this doesn't correspond to the physical reality, because for a given acceleration usually a maximum velocity is reached. Hence, consistent with fluid mechanics, a flow resistance F_W is introduced (Sigloch, 2009, S. 181). The flow resistance is usually proportional to the square of the absolute velocity v_N^2 at the position P_N. With the **drag coefficient** c_w the flow resistance is given by

$$F_W \propto v_N^2 \tag{6}$$

$$\vec{F}_W = c_w v_N^2 \vec{e}_{vN} \tag{7}$$

$\vec{e}_{vN}$ denotes the unity vector of the flow resistance. Finally, the equation for the movement of the pedestrian is defined by the addition of (5) and (7).

$$-\vec{\nabla}\phi_N^k - c_w v_N^2 \vec{e}_{vN} = m_p\vec{a}_N^k \tag{8}$$

Rearranging (8) with respect to $\vec{a}_N^k$ finally yields

$$\vec{a}_N^k = \frac{-\vec{\nabla}\phi_N^k - c_w v_N^2 \vec{e}_{vN}}{m_p} \tag{9}$$

(9) represents the dynamic model of the pedestrian. Two parameters are given, which are dependent on the expected dynamics of the pedestrian, the pseudo mass m_p and the drag coefficient c_w. These parameters have to be configured in a suitable way. Section 2.4 defines two boundary conditions for obtaining these parameters.

2.3 Sum of Acceleration Vectors

For each information source, an acceleration vector $\vec{a}_N^k$ is calculated at the position of the pedestrian. Under assumption of the independence of all information sources, the total acceleration of m information sources is calculated by the sum of all acceleration vectors a_N^k.

$$\vec{a}_N = \sum_{k=1}^{m} \vec{a}_N^k \tag{10}$$

The resulting total acceleration vector $\vec{a}_N$ of the pedestrian at the position P_N can be used for example as control unit $\mathbf{u_{k-1}}$ in a pedestrian prediction model as described in section 3.

2.4 Choice of Parameters

As consequence of (9), two parameters m_p and c_w are given, which are dependent on the dynamic of the pedestrian. Two boundary conditions shall be defined in order to obtain appropriate values for the two parameters m_p and c_w

1. **The pseudo mass m_p can be configured by using the absolute acceleration value a_R from standing still to walking for a given potential:** It follows from standing still ($v_N = 0$) and (8):
$$-\vec{\nabla}\phi_N^k = m_p \vec{a}_N^k \tag{11}$$
$$-\vec{\nabla}\phi_N^k = m_p a_N^k \vec{e}_{a_N^k} \tag{12}$$
The absolute value of the acceleration is given by
$$|\vec{\nabla}\phi_N^k| = m_p a_N^k \tag{13}$$
This finally yields
$$m_p = \frac{|\vec{\nabla}\phi_N^k|}{a_N^k} = \frac{|\vec{\nabla}\phi_N^k|}{a_R} \tag{14}$$
The acceleration a_R is defined by the person itself. Typical values are $a_R = 1\frac{\mathrm{m}}{\mathrm{s}^2} \ldots 3\frac{\mathrm{m}}{\mathrm{s}^2}$ (Tiemann, 2012, S.54 ff.) (Fugger et al., 2000, S. 24).

2. **The drag coefficient c_w can be obtained from its relationship with the absolute velocity v_R, which a pedestrian can reach for a given potential:** For $v_N > 0$ the derived (8) is given by
$$c_w v_N^2 \vec{e}_{v_N} = -\nabla\phi_N^k - m_p a_N^k \vec{e}_{a_N^k} \tag{15}$$
The absolute value is given by
$$c_w = \frac{|\vec{\nabla}\phi_N^k| + m_p a_N^k}{v_N^2} \tag{16}$$
Under the assumption, that the pedestrian reaches the maximum velocity the acceleration vector $a_N^k = 0$, therefore (16) reduces to
$$c_w = \frac{|\vec{\nabla}\phi_N^k|}{v_R^2} \tag{17}$$

3 PEDESTRIAN PREDICTION MODEL

In this section, a pedestrian prediction model is presented, which includes the model of section 2.

3.1 Pedestrian Prediction

The goal of a prediction algorithm is to determine the state (including the location) of an object, which mostly moves. In the special case of linear and noiseless state transition, the following prediction model can be used.

$$\mathbf{x_k} = \mathbf{F}\mathbf{x_{k-1}} + \mathbf{G}\mathbf{u_{k-1}} \tag{18}$$

State vector $\mathbf{x_k}$ in k-th time sample is calculated by multiplication of the state transition matrix $\mathbf{F}$ with the previous state vector $\mathbf{x_{k-1}}$. Additionally, there is an influence by the multiplication of the control matrix $\mathbf{G}$ and the control vector $\mathbf{u_{k-1}}$ in *(k-1)*-th time step. The prediction model is calculated on a physical level. So, it seems obvious to derive a physical control unit from the information sources. As pedestrians interact in a physical environment, which is in the case of gravitation and electric fields an acceleration field, it seems reasonable to assume in the following an acceleration as additional control input. In the proposed model $\vec{a}_N^k$ of (10) can be used as a control input $\mathbf{u_{k-1}}$ in (18).

For the prediction of the trajectories of a pedestrian, the following assumptions are made. The pedestrian moves with constant velocity and the input vector, given by the acceleration $\vec{a}_N$, is a location dependent acceleration vector, which is derived from the intention and the map information by the proposed model through (10). The model becomes

$$\begin{pmatrix} x_k \\ y_k \\ v_{x,k} \\ v_{y,k} \end{pmatrix} = \begin{pmatrix} 1 & 0 & \Delta t & 0 \\ 0 & 1 & 0 & \Delta t \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} x_{k-1} \\ y_{k-1} \\ v_{x,k-1} \\ v_{y,k-1} \end{pmatrix} + \begin{pmatrix} 0.5\Delta t^2 & 0 \\ 0 & 0.5\Delta t^2 \\ \Delta t & 0 \\ 0 & \Delta t \end{pmatrix} \begin{pmatrix} a_{x,N} \\ a_{y,N} \end{pmatrix} \tag{19}$$

where *(k-1)*-th state is used for for the prediction of the position x_k, y_k and the velocity $v_{x,k}$ in x-direction and $v_{y,k}$ in y-direction. Additionally, the control input $\vec{a}_N = (a_{x,N}, a_{y,N})$ influences the state of the pedestrian in time step k.

3.2 Information as Potential Fields

As information sources intention and map information are assumed. For each information source, the weight factor corresponding to section 2.1 has to be defined. The intention (information source 1 in the following) shall be modeled as a conic potential well with the constant parameter ρ

$$p^1(d^1_{iN}) = \rho d^1_{iN} \tag{20}$$

For the map information usually a exponentially decreasing weight factor is assumed (Heinemann et al., 2006; Luber et al., 2010). Beside of the two parameters c_w and m_P, a third parameter is introduced, which defines the ratio between the intention and the map information. So, the map information (information source 2 in the following) is defined by

$$p^2(d^2_{iN}) = s_i e^{-\frac{1}{s_i} d^2_{iN}} \tag{21}$$

s_i can be interpreted as the influence factor of the map information. If the coefficient of the intention field (target area) is set to $\rho = e^{-1}$, then the factor s_i can be interpreted as the influence area of the obstacle i. In other words s_i defines the distance, in which the acceleration of the constant decreasing intention field equals the field of the obstacle and hence no acceleration of the intention field is present at the position of the pedestrian in distance s_i to the object.

Corresponding to section 2.2 the parameters c_w and m_P are set on behalf of the intention field, i.d. $|\vec{\nabla}\phi^2_N| = e^{-1}$ is set in (14) and (17). For the two boundary conditions, $a_R = 1\frac{m}{s^2}$ and $v_R = 1.4\frac{m}{s}$ are chosen. The acceleration $a_R = 1\frac{m}{s^2}$ equals the acceleration of the transition from standing to walking in recent research (Tiemann, 2012, S.54 ff.) (Fugger et al., 2000, S. 24). The maximum velocity for a free-walk is set to $v_R = 1.4\frac{m}{s}$, which equals the average velocity of a pedestrian (Wakim et al., 2004). The obstacle parameter s_1 for the staircases (object 1) is set to $s_1 = 0.5\ m$.

3.3 Summary

A summary of the model is depicted in figure 1 at an abstract level. Its goal is to derive from the information sources an acceleration vector. Every information source represents a potential field. For every potential field, the gradient is calculated and from the gradient, the acceleration vector is derived, which is used as a control unit in the proposed tracking algorithm (c.f. (18)). a^1_N denotes the acceleration contribution of the first information source at the position $P_N(x_N, y_N)$ of the pedestrian.

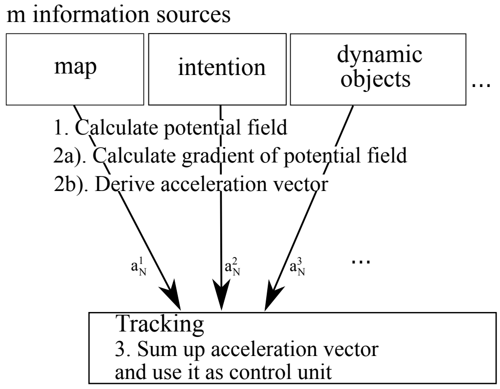

Figure 1: Overview of the proposed model.

4 EVALUATION OF THE PREDICTION MODEL

The introduced model shall be configured for a concrete scenario. For this purpose, the free available data sets from The University of Edinburgh School of Informatics (Edinburgh Informatics Forum Pedestrian Database, 2010) were used as reference trajectories. The data sets consist of trajectories of people in a forum, which were detected by a camera. In figure 2 a frame of the camera is depicted.

Figure 2: Overview of the Informatics Forum in the School of Informatics at the University of Edinburgh. Red arrows mark the different entrances of the forum. Original photo from (Edinburgh Informatics Forum Pedestrian Database, 2010).

4.1 Pedestrian Scenario

In order to evaluate the efficiency of the proposed model, the given data set was filtered by a scenario, in which the pedestrian only has got one goal and an obstacle in his way. Therefore, the way between the lower right corner of the forum to the “Second part” near the stair cases is chosen (c.f. figure 2). Only trajectories of single person (no groups) are taken and it is assumed that there are not any dynamic interactions between pedestrians. As a result of this selection, 100 trajectories are chosen, which were used for the validation of the model. Figure 3 shows a plot of all analyzed trajectories.

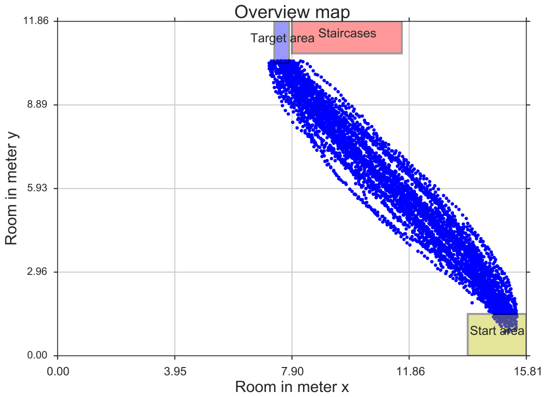

Figure 3: Plot of all trajectories extracted from the data set in Informatics Forum. Every trajectory starts in the starting area and ends in the target area. The staircases are abstracted as a rectangular obstacle.

4.2 Experimental Results

For the initial condition $k = 0$, the position of the state vector is set to the first position of the real observed trajectory. The velocity vector is approximated by linear regression of the first ten data points of the real observed trajectory.

Based on the prediction model, trajectories for all selected data sets were predicted. It is obvious that both trajectories almost match at the start. This is due to the fact that the initial conditions are quite the same. Other prediction steps are only calculated based on the intention and map information, that are the target area and the single obstacle “staircases” in this scenario. There is no additional update nor correction of the observed trajectory. This can be interpreted in the way that no further measurements beside the measurement of the initial condition are assumed.

In Figure 4 all extracted trajectories and corresponding predicted trajectories are plotted. For an objective evaluation, the root mean square error (RMSE) between the real and the observed trajectories is calculated.

As the predicted trajectory is more dense than the observed trajectory, the distance of every data point of the observed trajectory to the nearest data point of the predicted trajectory is calculated. The mean value of all data points of all trajectories is calculated and denoted as RMSE. For 100 trajectories, D_i data points of the i-th observed trajectory and the minimum distance between the observed and predicted trajectory d_{ij} for the j-th data point the RMSE is given by

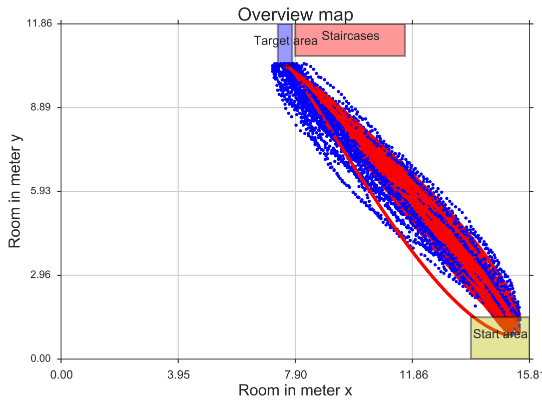

Figure 4: Plot of all extracted trajectories from the data set in Informatics Forum (blue dots) and the predicted trajectories (red dots).

$$\mathrm{RMSE} = \frac{1}{100} \sum_{i}^{100} \frac{1}{D_i} \sum_{j}^{D_i} d_{ij} \tag{22}$$

In Figure 5 the course of d_{ij} for two example trajectories $i = 20$ and $i = 40$ is depicted. As the starting condition of the prediction is initialized with the first point of the observed trajectory, both trajectories have got a difference of $d_{ij} = 0$ for $j = 0$. In dependence on the real movement of the pedestrian d_{ij} rises to a maximum of $0.3\ \mathrm{m} \ldots 0.6\ \mathrm{m}$. The curve declines till the end, as both curves end in the target area.

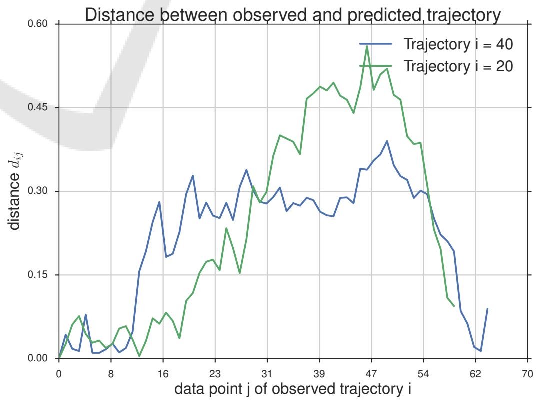

Figure 5: Difference between the observed and the predicted trajectory d_{ij} for two example trajectories $i = 20$ and $i = 40$.

For the given scenario a $RMSE \approx 0.29$ m is obtained. These are very good results. Further improvements could be possible, if planning for the pedestrians is assumed. In this simple scenario the behavior of the pedestrians is only reactive to obstacles. This means, that the pedestrian goes in the direction of the goal until he meets an obstacle and then surrounds the obstacle in the direction of the potential gradient.

5 CONCLUSIONS

Typical mathematical models for the fusion of information sources have got many parameters, which has to be learned automatically by real world scenarios. In this paper, the information sources are modeled as potential fields accelerating a pedestrian in the field, which minimizes the number of parameters and gives an intuitive interpretation of them. The proposed model is configured for a simple real world scenario. In this scenario, two information sources, the intention and the map information, are considered. The model is evaluated using real camera based trajectories. The RMSE is calculated and shows a deviation of 0.29 m between the predicted and observed trajectory. For future research more complex scenarios can be considered. These scenarios shall include multi-hypotheses and more information sources like dynamic pedestrian interactions and group behaviors.

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